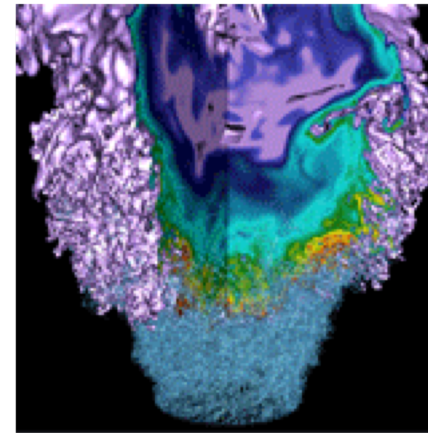
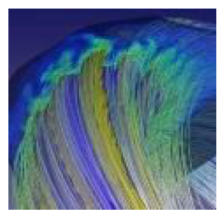
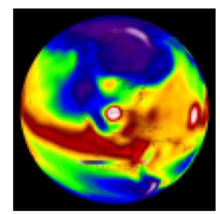
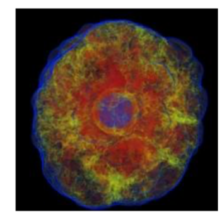
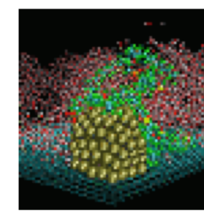
Machine Learning for Climate Extremes: Training is Everything











William Collins*, Prabhat, and Ankur Mahesh

*LBNL and *UC Berkeley*

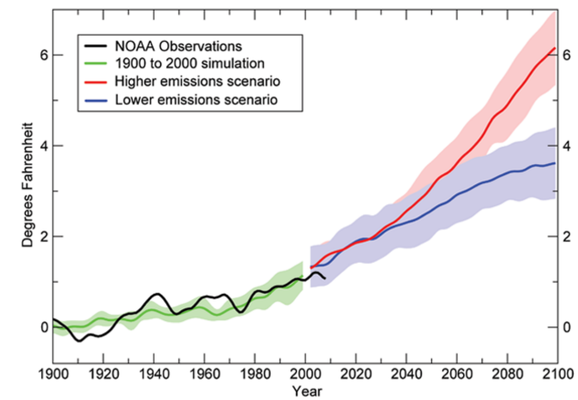
The CASCADE Project

The Gordon Bell Team

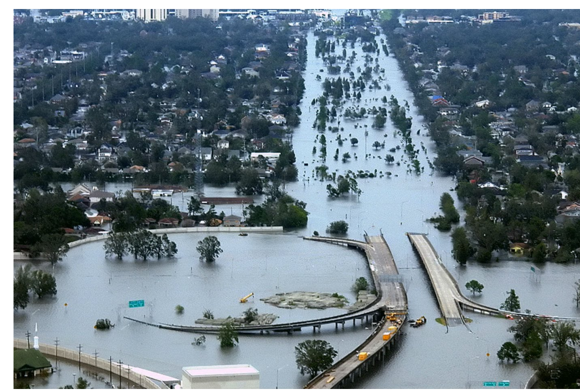
NERSC Data and Analytics Services

Characterizing Climate Change

- **How will the mean climate change by 2100?**
  - will the globe warm up by 1.5 or 2.0 C?
  - will the sea level rise by 1 or 2 feet?
  -



- **How will extreme weather change by 2100?**
  - Will there be more storms (TC, ETC, AR)?
  - Will storms make landfall more often?
  - Will storms become more intense?
  - Will storms carry more water?



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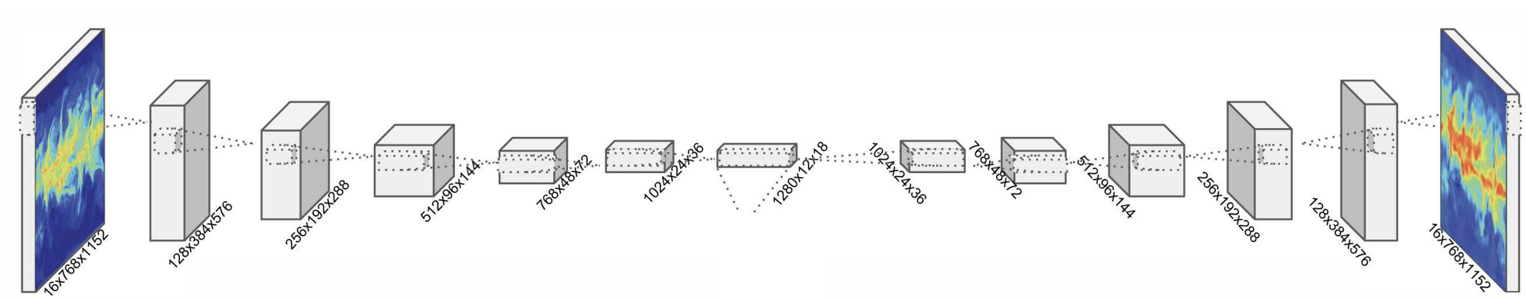
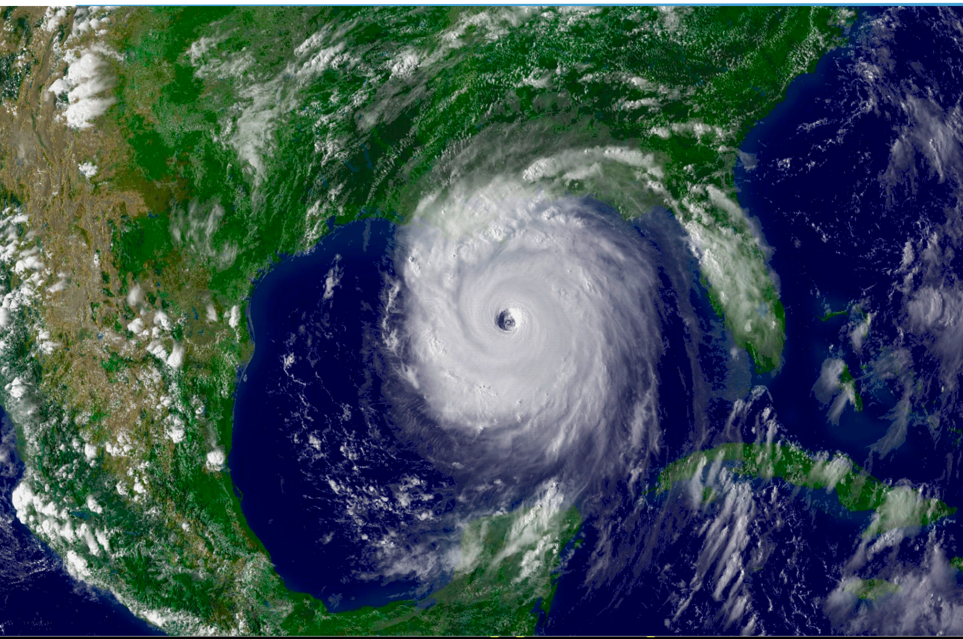
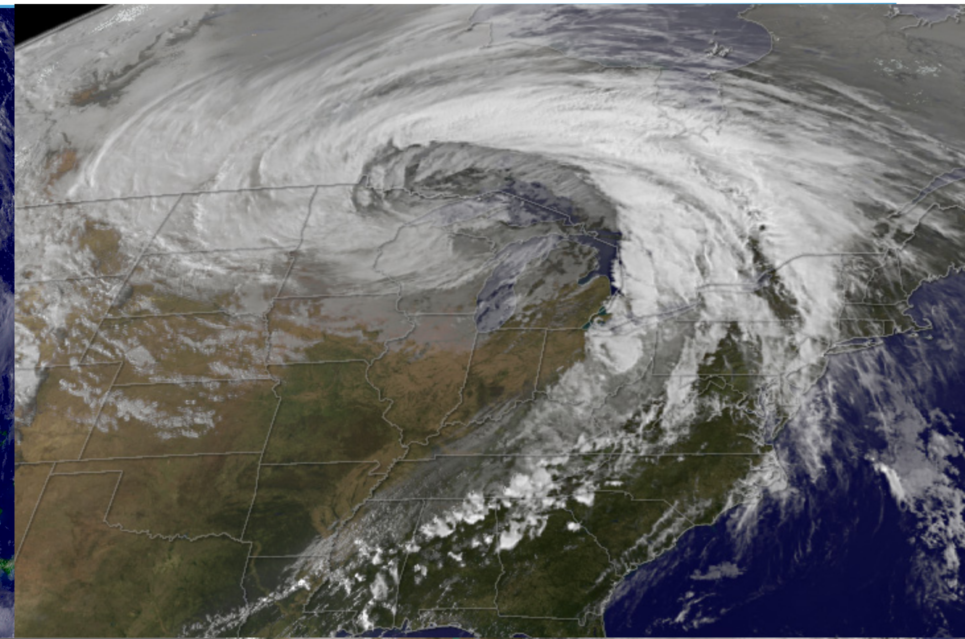
Roadmap

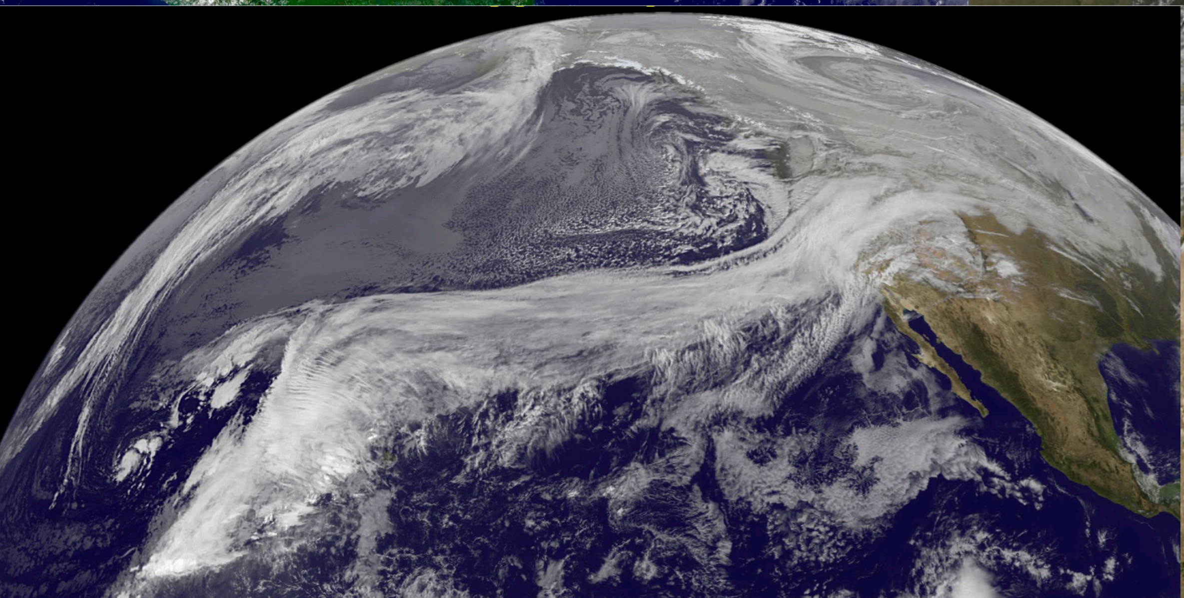
- Extreme phenomena of interest
- Types of classification / categorization
- Typical input data from Earth System Models
- Supervised algorithms to detect these extremes
- Semi-supervised algorithms to detect extremes
- Training climate classifiers at Exascale
- Future directions for machine learning and extremes

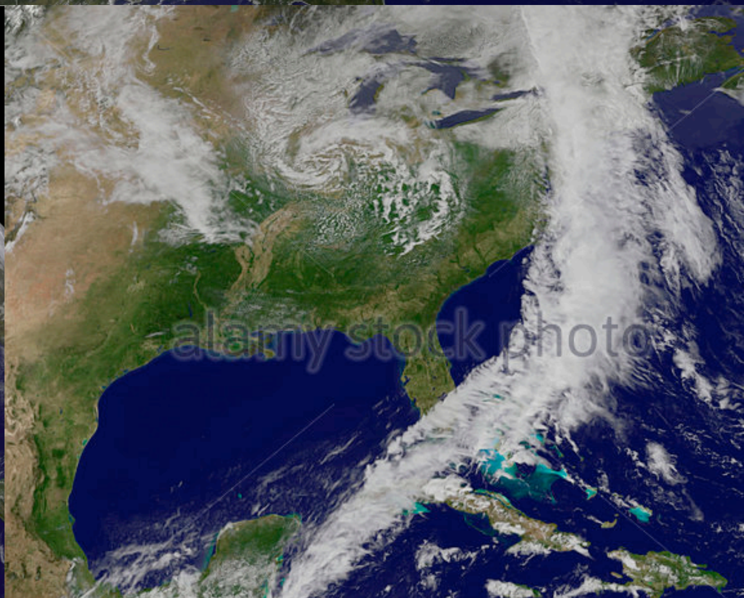


Characterizing Extreme Weather…



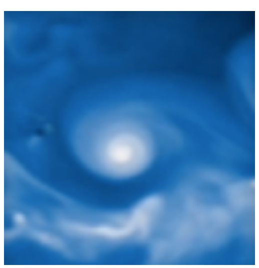






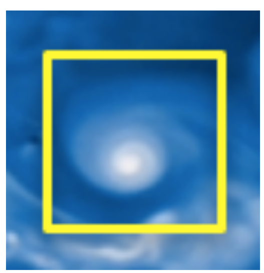
Climate Science Tasks

Classification



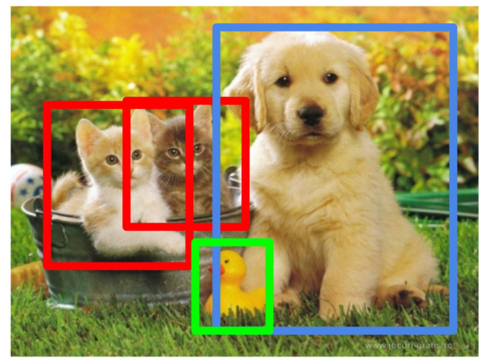
Liu, et al
ABDA'16

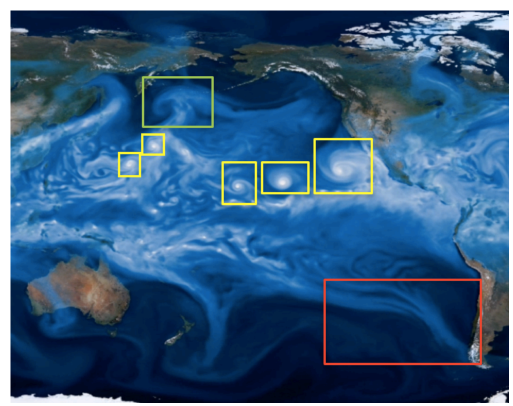
Classification + Localization



Racah, et al
NIPS'17

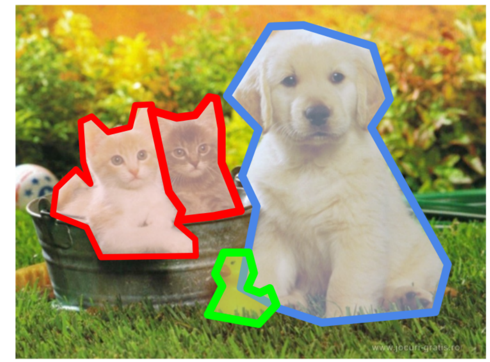
Object Detection

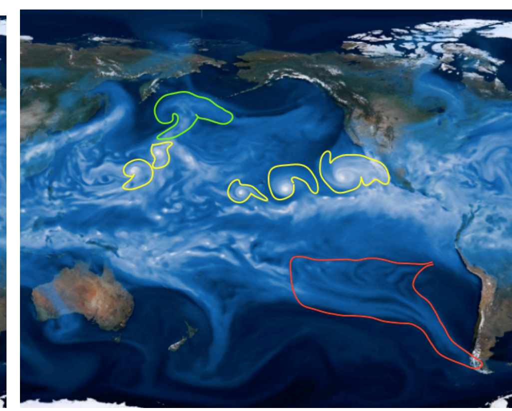




Racah, et al, NIPS'17
Kurth, et al, SC'17

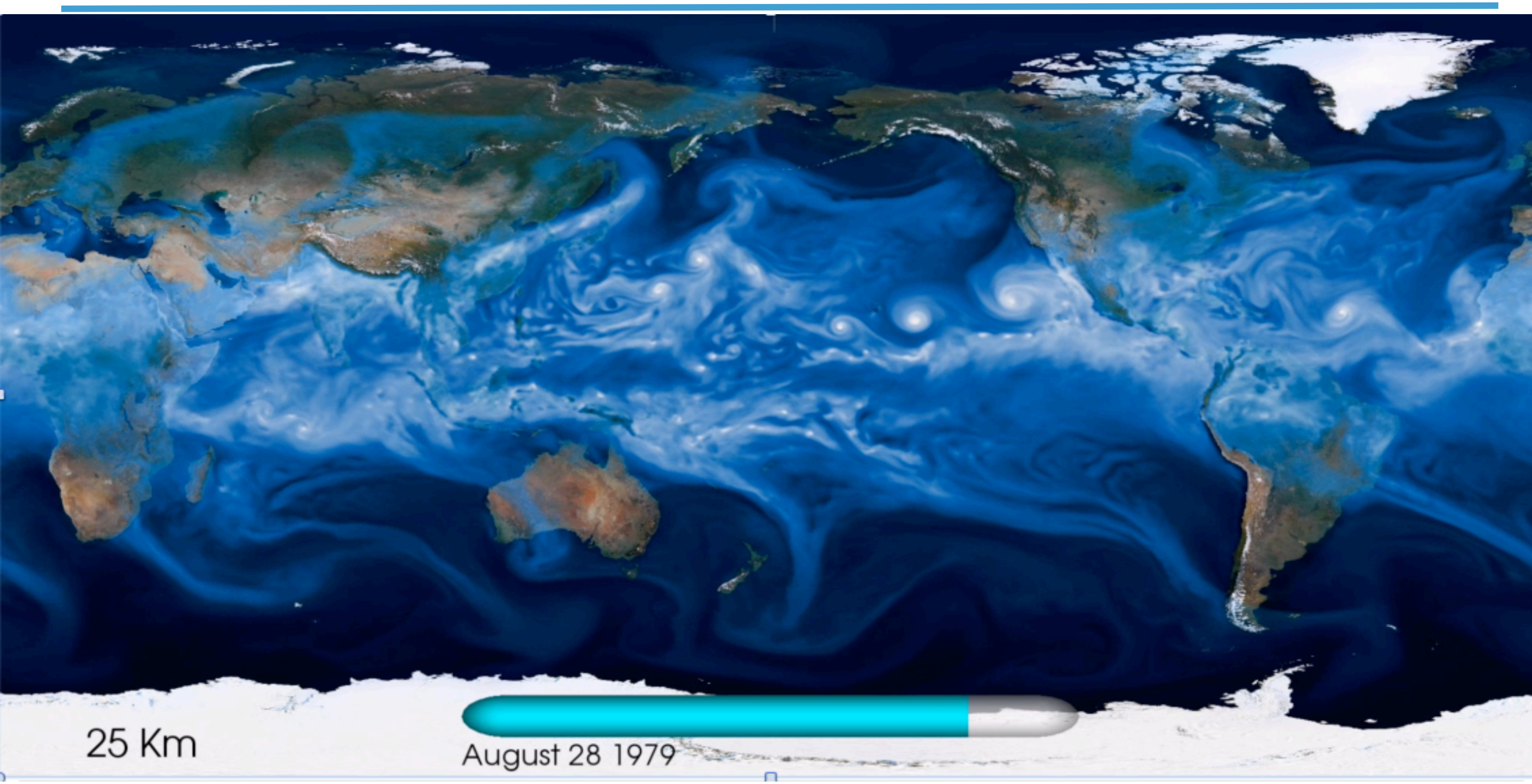
Instance Segmentation





Kurth, et al, SC'18

CAM5 0.25-degree simulation data



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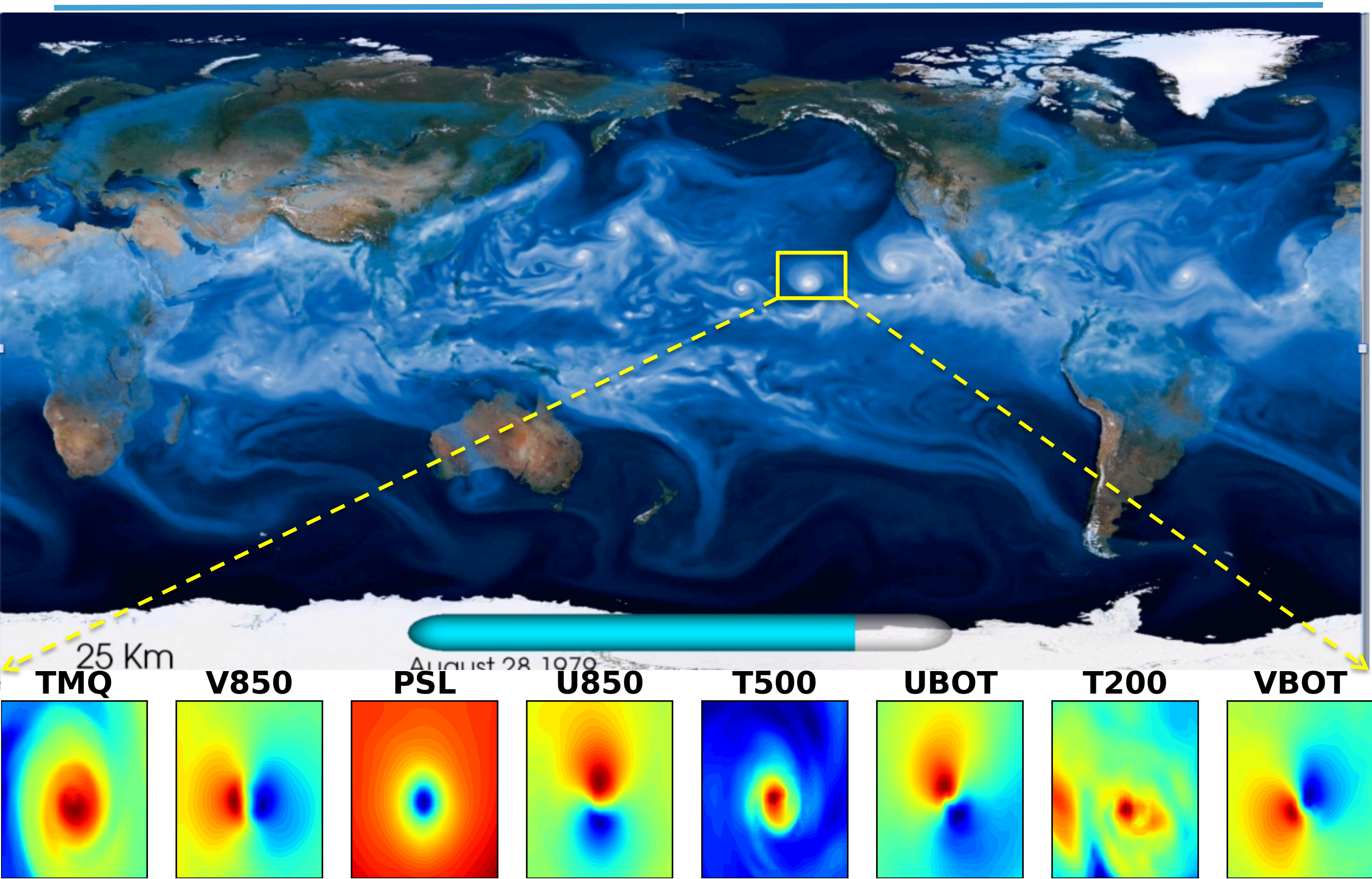
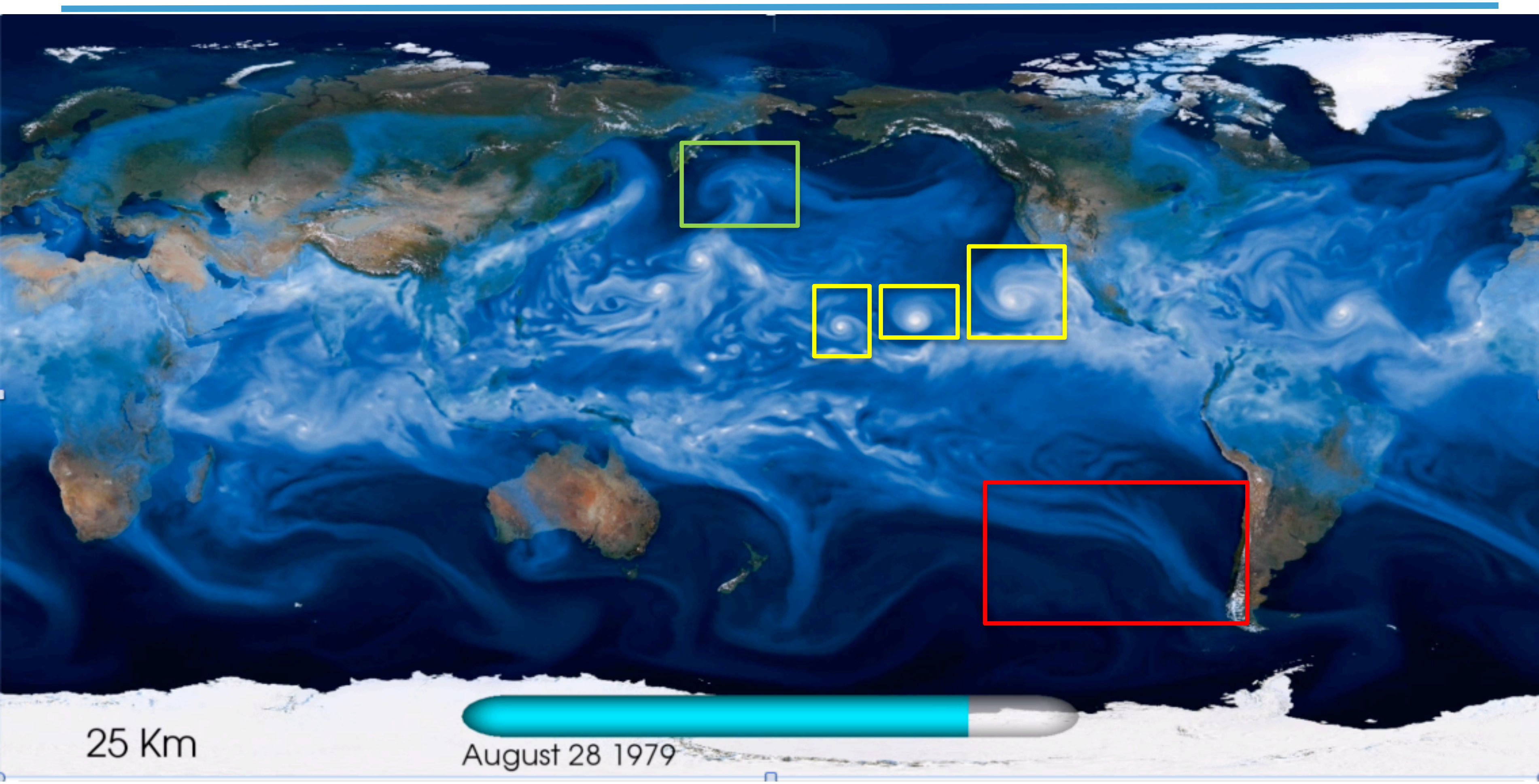
Challenge: Multi-Variate Data



Task: Find Extreme Weather Patterns



Supervised Learning

- **Training Input: Cropped, Centered, Multi-variate patches with Labels***
  - –Tropical Cyclone (TC)
  - –Atmospheric River (AR)
  - –Weather Front (WF)

*Labels are provided by TECA, which in turn implements human-specified criteria

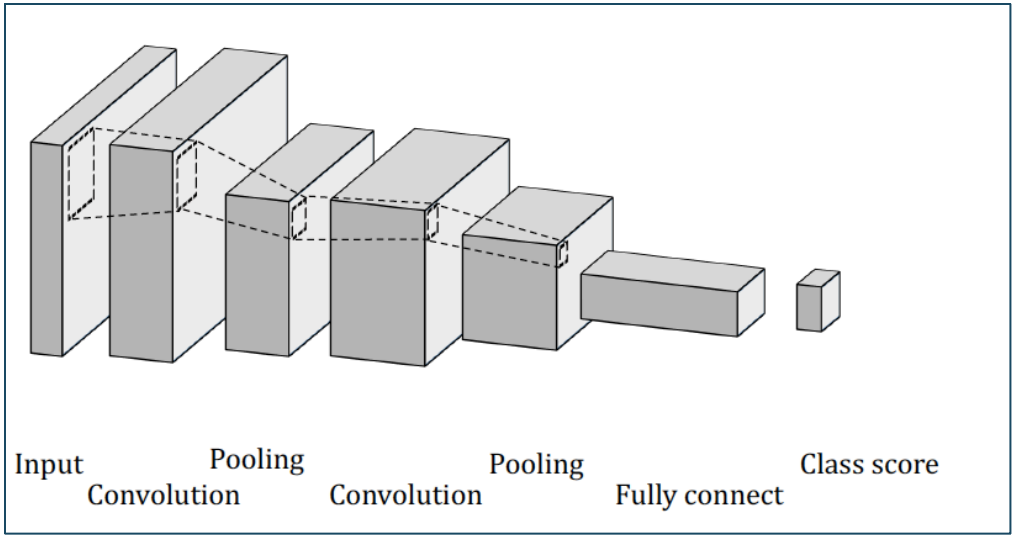
- **Output: Binary (Yes/No) on Test patches**
  - – Is there a TC in the patch?
  - – Is there an AR in the patch?
  - – Is there a WF in the patch?

Training Data

CLASSIFICATION	Image Dimension	Variables	Total Examples (+ve)	(-ve)
Tropical Cyclone	32x32	PSL,UBOT,VBOT,TMQ, U850,V850,T200,T500	10000	10000
Atmospheric Rivers	148x224	TMQ, Land Sea mask	6500	6800
Weather Fronts	27x60	T2m, Precip, PSL	5600	6500

Supervised Convolutional Architecture

CLASSIFICATION	Conv1	Pool1	Conv2	Pool2	Full	Full
Tropical Cyclone	5x5-8	2x2	5x5-16	2x2	50	2
Atmospheric River	12x12-8	3x3	12x12-16	2x2	200	2
Weather Fronts	5x5-16	2x2	5x5-16	2x2	400	2



Supervised Classification Accuracy

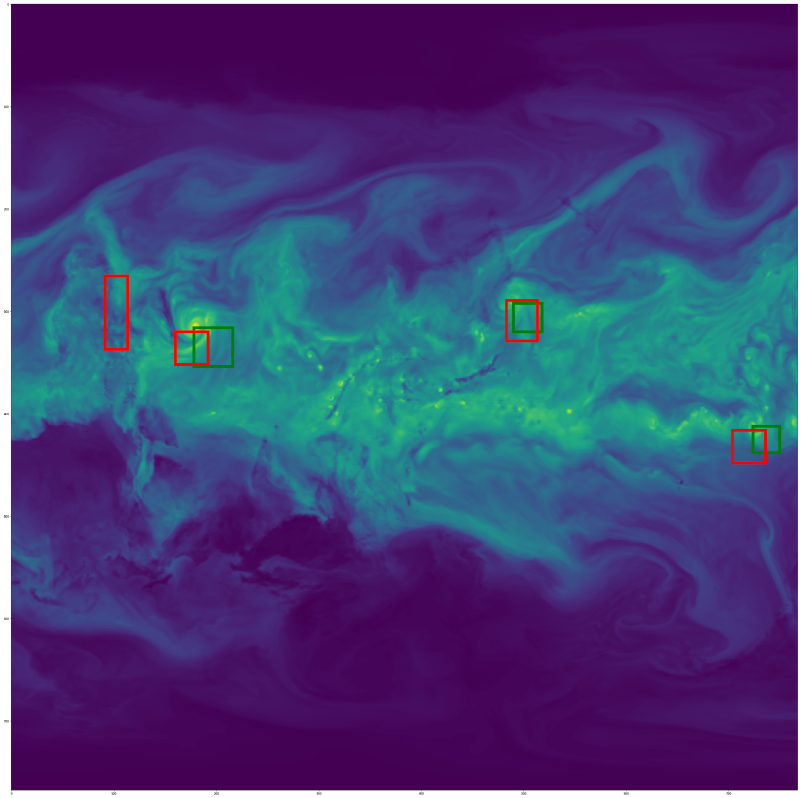
	Logistic Regression		K-Nearest Neighbor		Support Vector Machine		Random Forest		ConvNet	
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
Tropical Cyclone	96.8	95.85	98.1	97.85	97.0	95.85	99.2	**99.4**	99.3	**99.1**
Atmospheric Rivers	81.97	82.65	79.7	81.7	81.6	83.0	87.9	88.4	90.5	**90.0**
Weather Fronts	84.9	89.8	72.46	76.45	84.35	90.2	80.97	87.5	88.7	**89.4**

Hyper-parameter optimization applied with Spearmint for all methods

Semi-Supervised Machine Learning

Objectives:

- Want to predict bounding box location for weather pattern
- Want to discover new patterns despite few/no labels for several weather patterns
- Create unified architecture for all weather patterns



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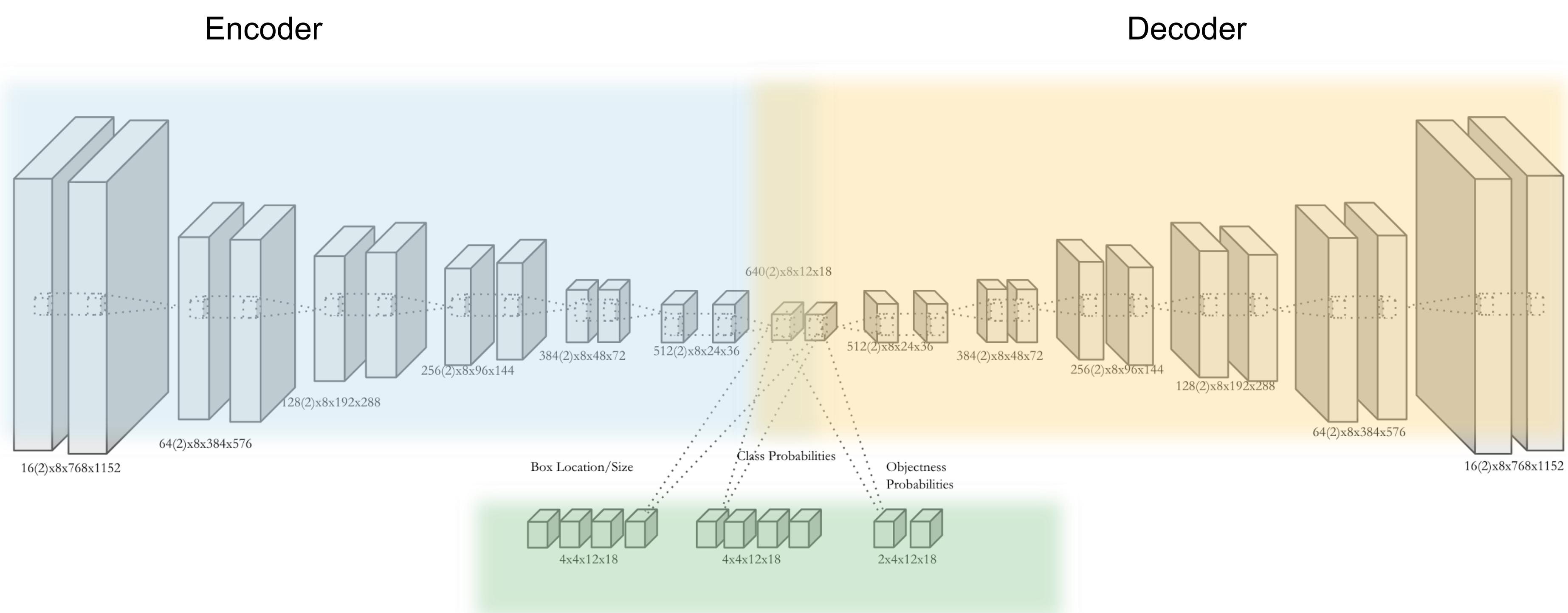
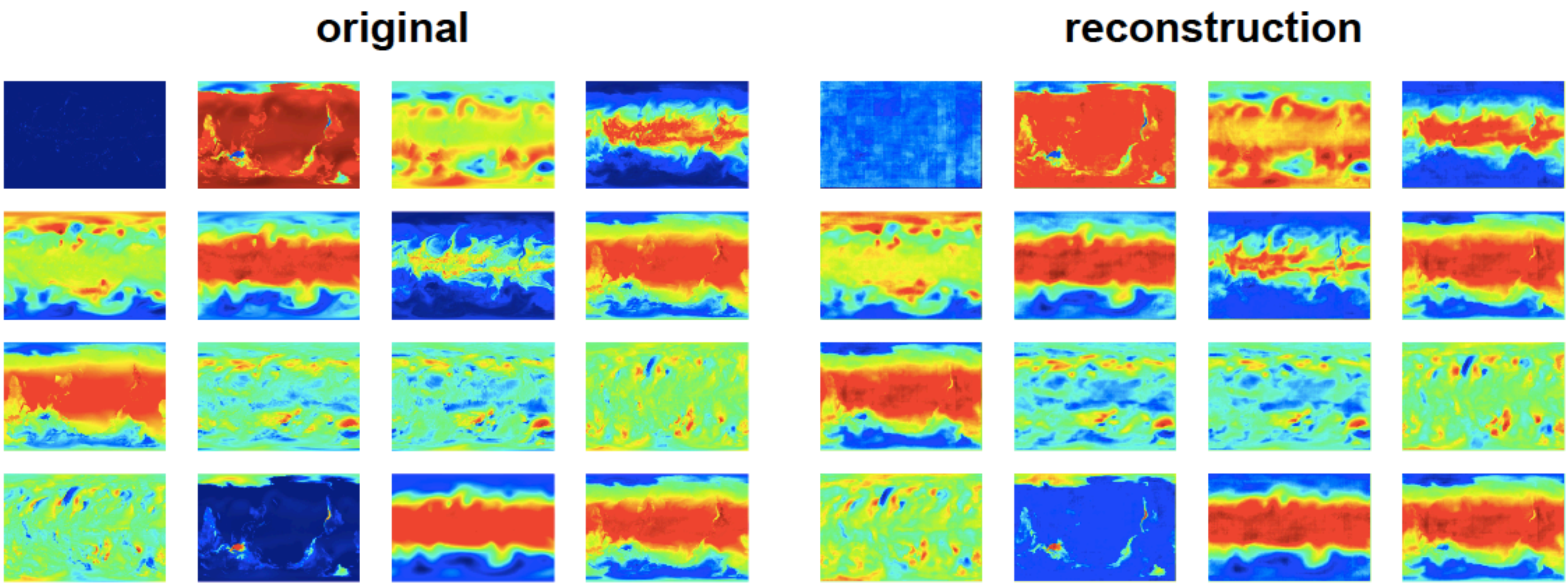
Semi-Supervised Convolutional Architecture

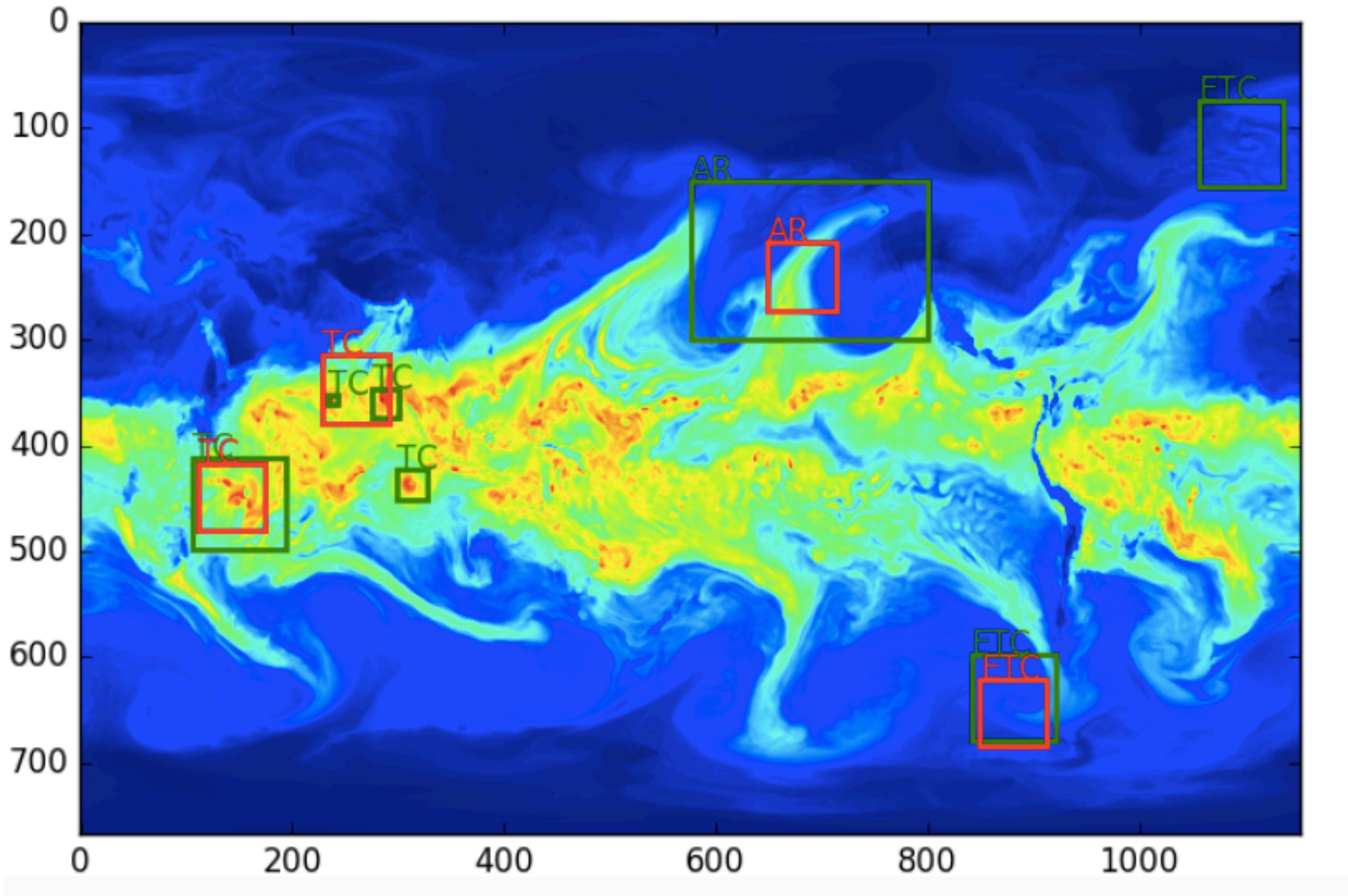


Classification + Bounding Box Regression

Reconstruction Results



Classification + Regression Results



Ground Truth
Prediction

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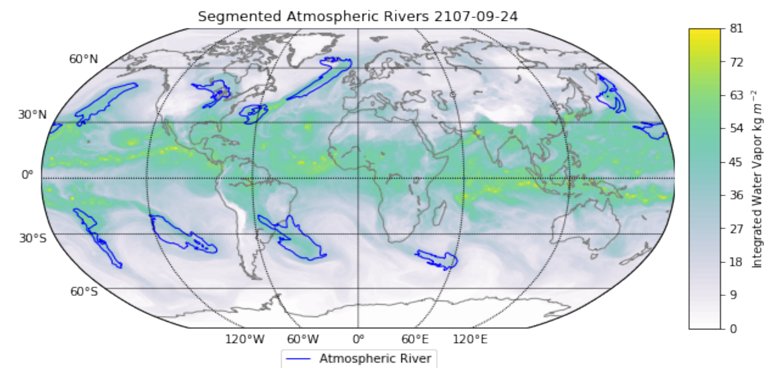
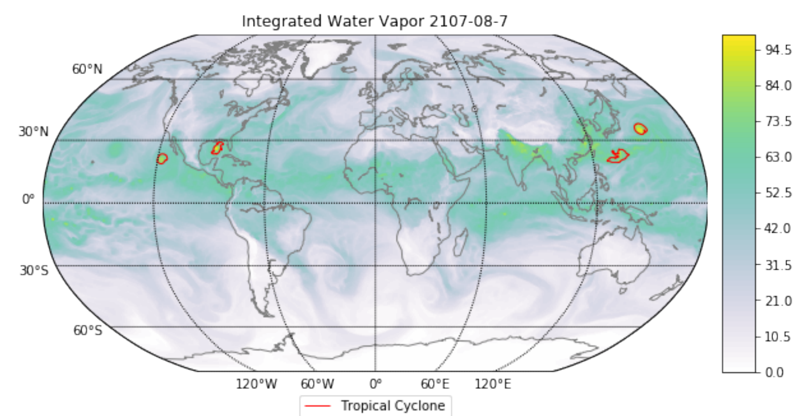
Training at Exascale: Climate Dataset

- **CAM5 0.25-degree output**
  - 1152x768 pixels, 3-hr
  - 16 variables
  - 20 TB
- **Ground Truth Labels for TC and AR**
  - Heuristics for detection followed by mask creation
- **Formulate segmentation problem**
  - 3 classes - background, TC and AR
  - high imbalance - most pixels are background high variance - shape of events change over time and in-between themselves



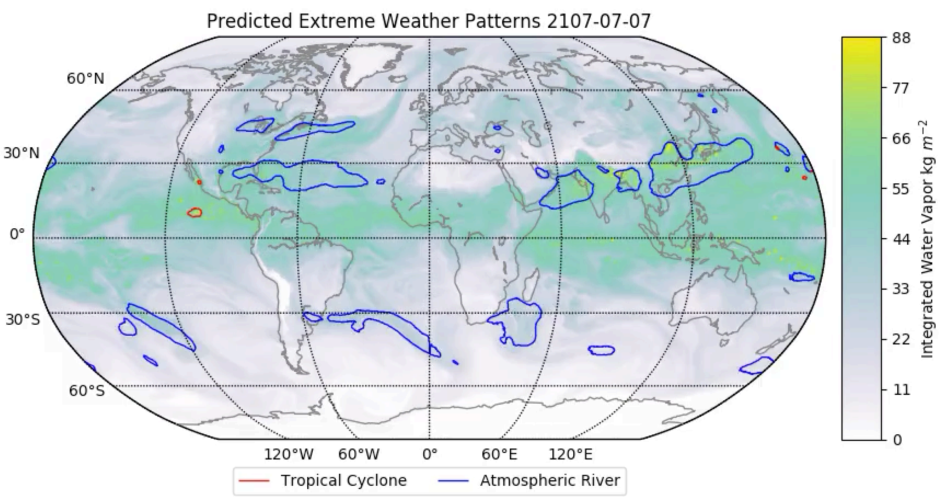


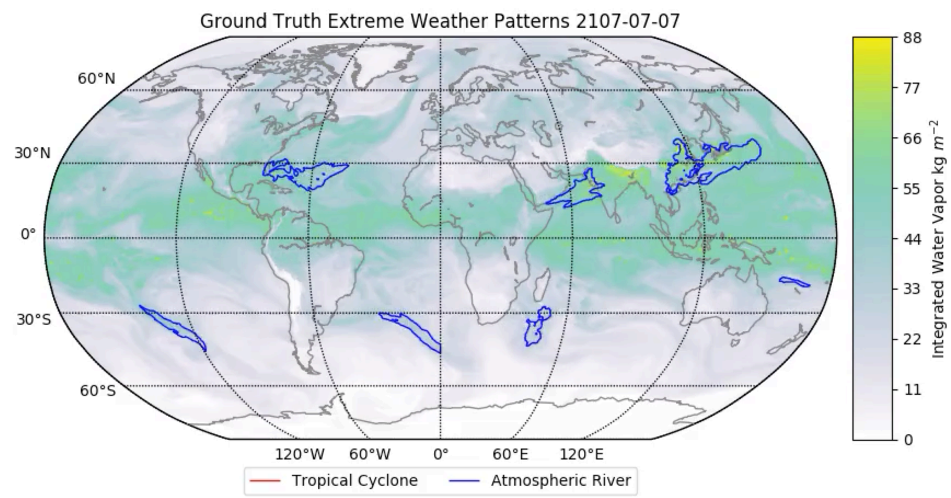
Training at Exascale Hardware: Summit

- Leadership class HPC system at OLCF, ranked #1 on Top500
- 4608 nodes with 2 IBM Power 9 CPU and 6 Nvidia Volta GPU
- 300 GB/s NVLink connection
- 800 GB NVMe storage/node
- Infiniband network; fat-tree topology
- ~3.45 ExaFlop theoretical peak (FP16)

Training code stresses all above components of the system

Segmentation Animation





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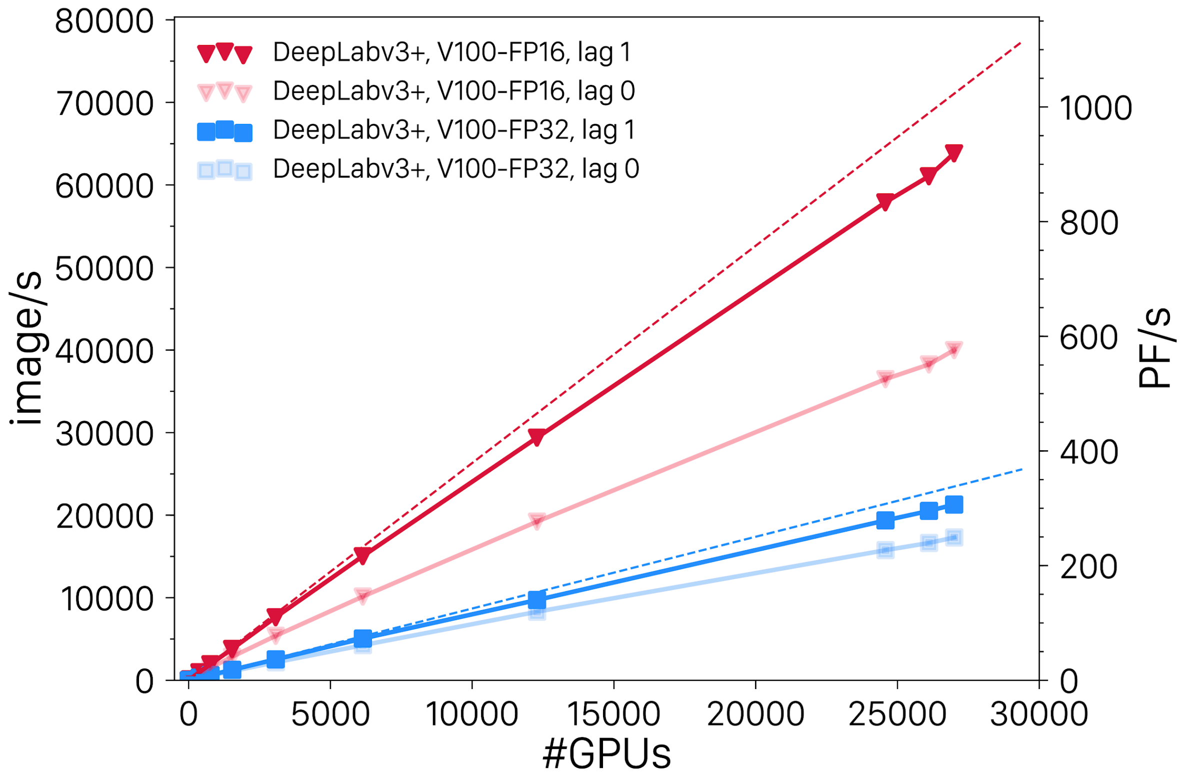
Extreme Scaling



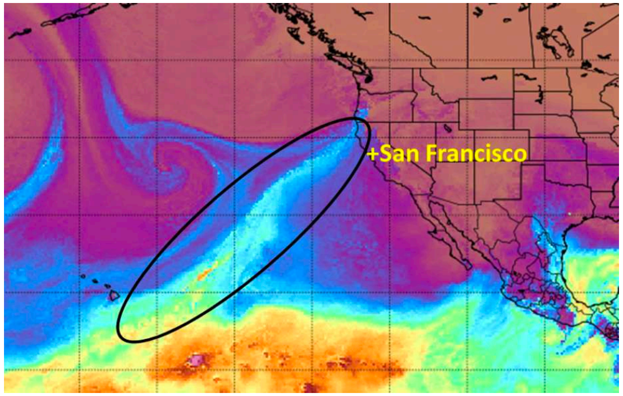
- 4560 Summit nodes, 27,360 Volta GPUs
- **1.13 EF** peak performance (16-bit)

Deep Learning for Detecting Extremes: Definitions Matter

- Atmospheric Rivers (ARs): "long, narrow, and transient corridors of strong horizontal water vapor transport…" *(AMS Glossary)*

- No community-accepted standard for identifying atmospheric rivers

  "You know one when you see one" – *ARTMIP 2018 Participant*



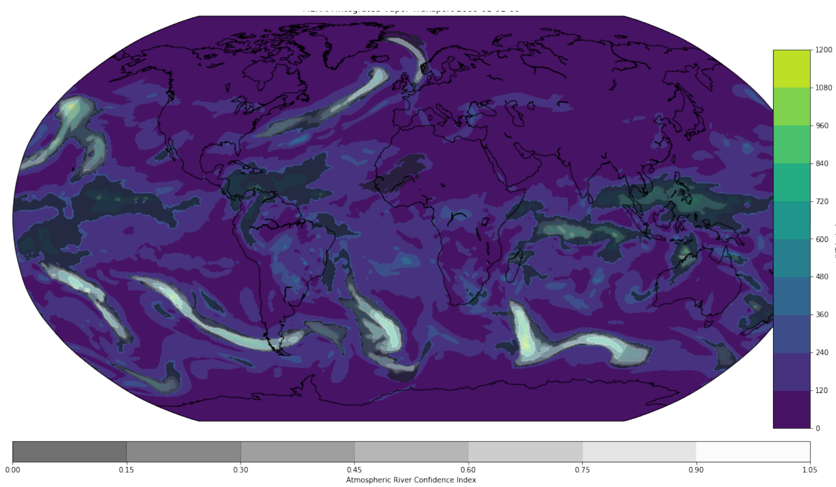
An AR off the coast of California. Source: TheGuardian

The ARTMIP Dataset

- The Atmospheric River Tracking Method Intercomparison Project (ARTMIP) includes AR detections from 14 algorithms in MERRA reanalysis data

- We explore CNNs' ability to detect ARs in different fields: *precipitable water* and *Integrated Vapor Transport*

- We explore CNNs' ability to detect ARs in different datasets: *MERRA* reanalysis and *CAM5* climate model



MERRA Integrated Vapor Transport 2000-01-01-00, shown with the mean of the 14 ARTMIP algorithms.

Shields, C. A., Rutz, J. J., Leung, L.-Y., Ralph, F. M., Wehner, M., Kawzenuk, B., … Nguyen, P. (**2018**). Atmospheric River Tracking Method Intercomparison Project (ARTMIP): project goals and experimental design. *Geoscientific Model Development*, *11*(6), 2455–2474. http://doi.org/10.5194/gmd-11-2455-2018

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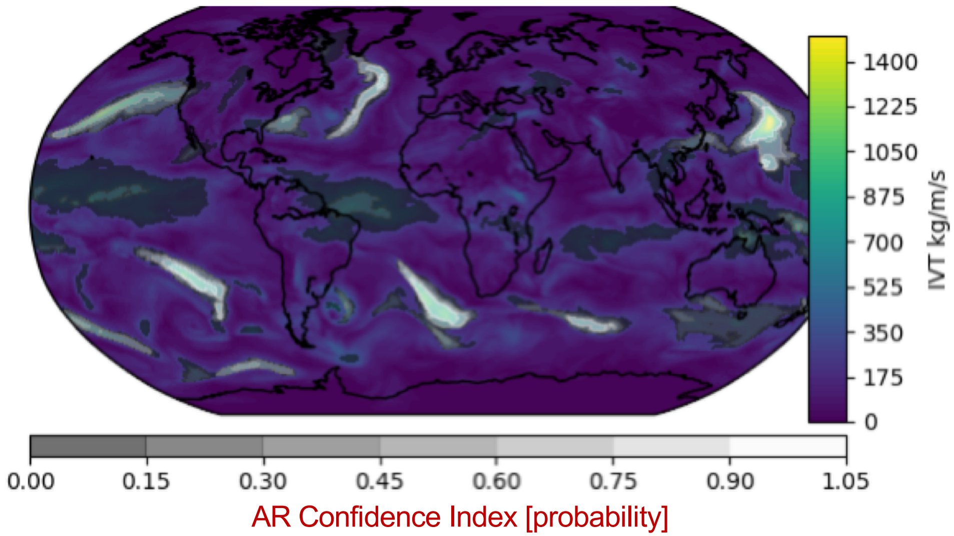
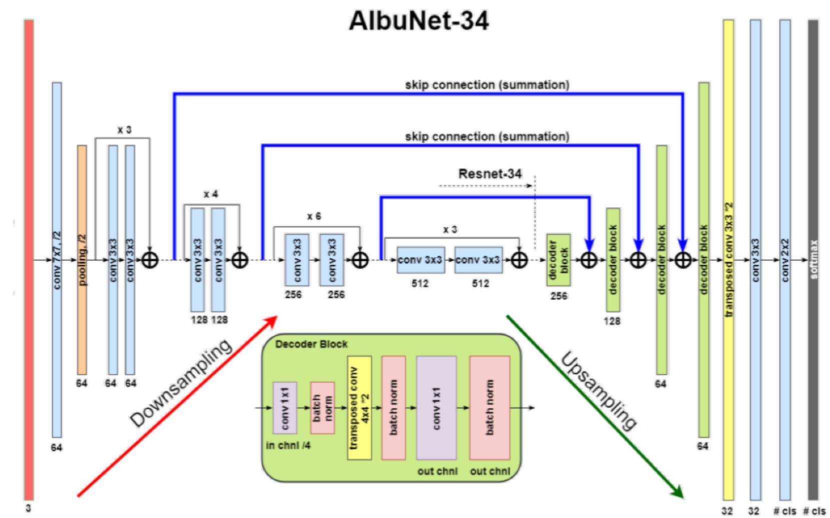
Can CNNs do Probabilistic ‘Segmentation’?

Input Field: Integrated Vapor Transport (IVT)
Output Field: AR Confidence Index [probability]





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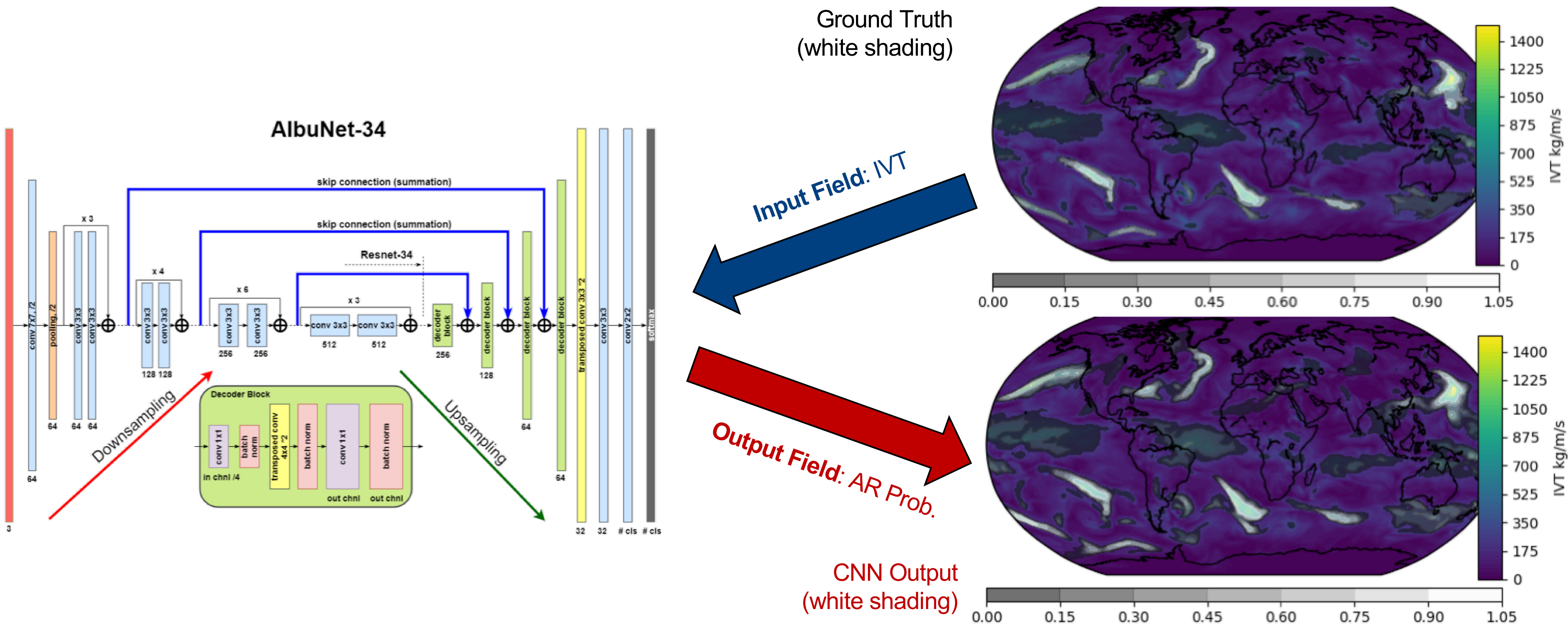
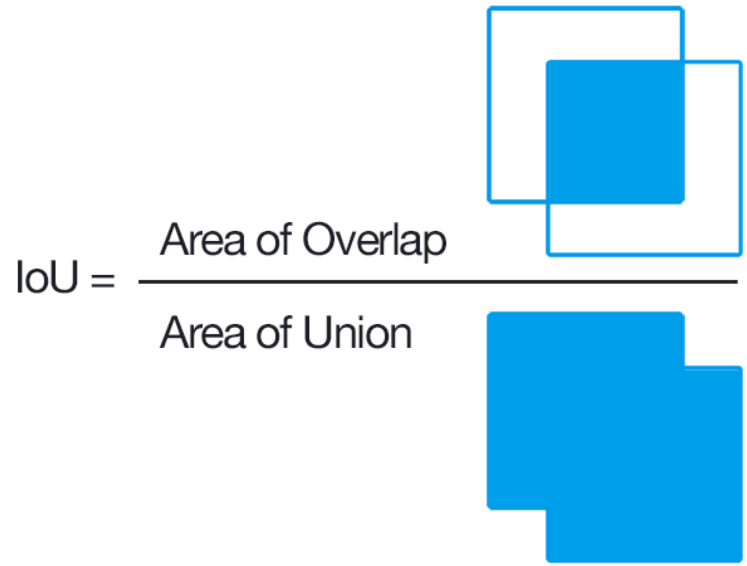
CNNs *Can* do Probabilistic Segmentation



Evaluating the Neural Network

- Intersection over Union: a scale from 0 to 1 representing the similarity between the DL prediction and the ARTMIP labels
- Neural network trained on Integrated Vapor Transport: 0.90
- Neural network trained on Precipitable Water: 0.81



Source: PyImageSearch

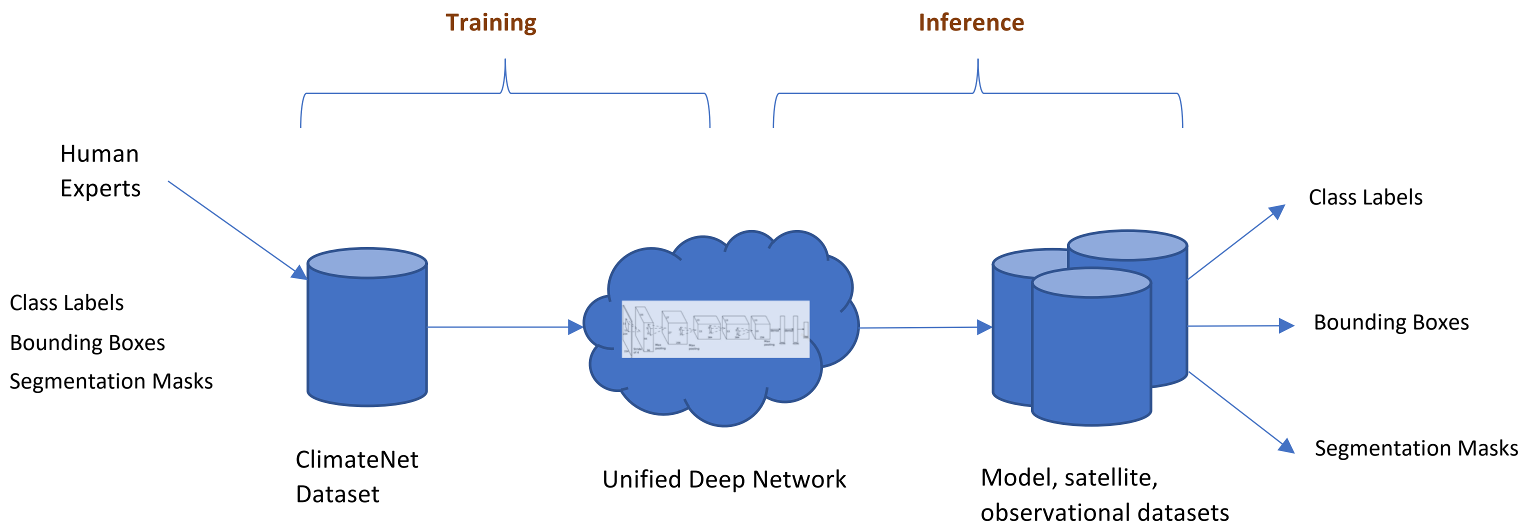
Key Advantages of Deep Learning

- A single CNN detection algorithm can represent the uncertainty characterized by 14 AR detection algorithms

- CNNs can identify high-quality ARs from precipitable water, while most other tracking algorithms require a more memory-intensive field: Integrated Vapor Transport

- CNNs can identify ARs in different categories of datasets (e.g. low-resolution, high-resolution, reanalysis, and future climate models)

ClimateNet: A path forward for labeled climate data



- Avoid heuristics; establish ground truth dataset for weather patterns
- Share both dataset + reference DL architectures w/ the community

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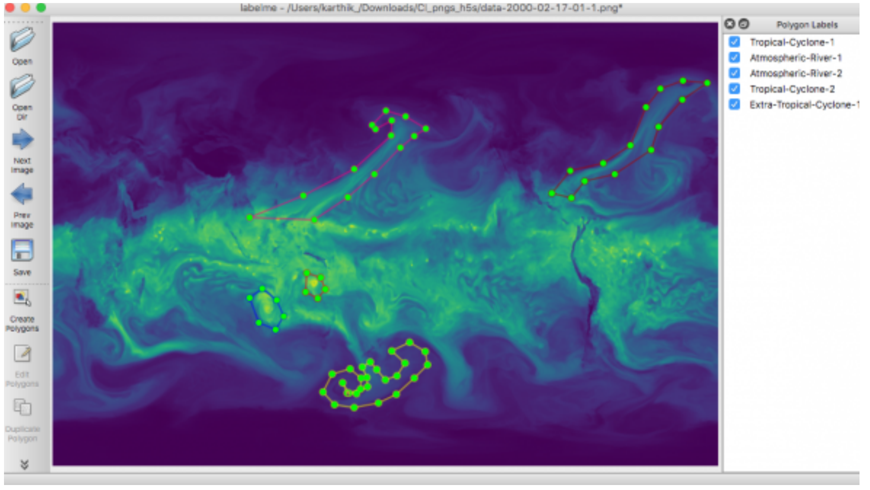
ClimateNet Interface

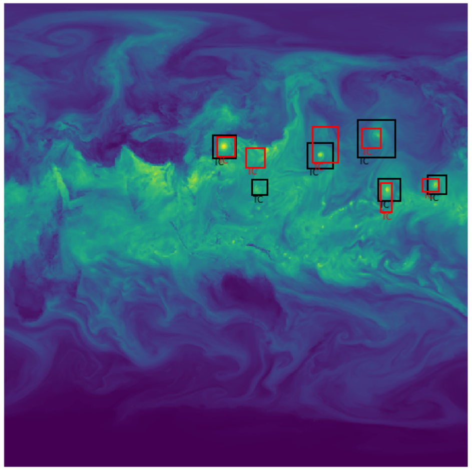
- **Avoid heuristics**
  - –Computer vision community 1980-2010
- **Ground Truth specified by experts using web interface**
  - –Tropical Cyclones
  - –Atmospheric Rivers
  - –Extra-tropical Cyclones
  - –...



- https://www.nersc.gov/research-and-development/data-analytics/big-data-center/climatenet/

Conclusions

- **Machine Learning is viable for Pattern Detection in Climate Data:**
  - Truth data sets from experts or hand-tuned algorithms
  - Supervised architectures can match their detection accuracy
  - Semi-supervised architectures may discover new patterns
- **Training of Deep Learning is amenable to acceleration:**
  - Fast, hybrid methods for parameter optimization
  - Moderns libraries enable good performance and scaling
- **Continuing challenges:**
  - Scarcity of labeled data: Need labeling “campaigns”
  - Interpretability and Visualization: ‘Black Box’ classifier
- **Opens the door to semantic segmentation of climate datasets**



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Open Challenges

- **Handling Complex Data**
  - 2D/3D/4D, graph, sparse/dense, multi-spectral
- **Lack of Theory (Machine Learning)**
  - Limits of supervised, unsupervised, semi-supervised learning
- **Lack of Theory (Climate Science)**
  - Unambiguous definitions of phenomena of interest
- **Interpretability**
  - Incorporating domain science principles (physical laws)
- **Uncertainty Quantification**

Acknowledgements

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Questions?